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Adapting crop rotations to climate change in regional impact modelling assessments

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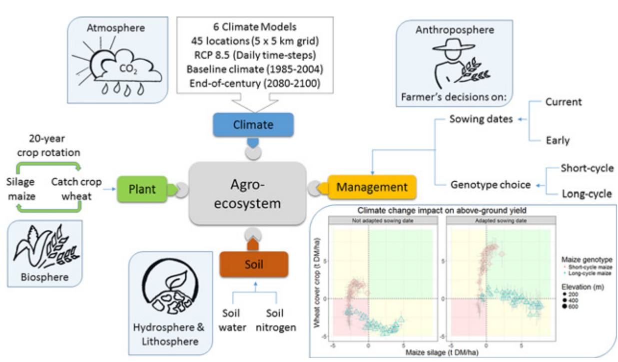
HIGHLIGHTS

- We assess spatial variability in adaptation of crop rotations to climate change.
- Climate change impacts differed depending on how adaptation was represented.
- Adaptation of one crop had carryover effects on following crops of the rotation.
- Rotation responses to climate change and adaptation were spatially variable.
- Results illustrate methodological aspects to adapt rotations in spatial assessments.

GRAPHICAL ABSTRACT



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ABSTRACT

The environmental and economic sustainability of future cropping systems depends on adaptation to climate change. Adaptation studies commonly rely on agricultural systems models to integrate multiple components of production systems such as crops, weather, soil and farmers' management decisions. Previous adaptation studies have mostly focused on isolated monocultures. However, in many agricultural regions worldwide, multi-crop rotations better represent local production systems. It is unclear how adaptation interventions influence crops grown in sequences. We develop a catchment-scale assessment to investigate the effects of tactical adaptations (choice of genotype and sowing date) on yield and underlying crop-soil factors of rotations. Based on locally surveyed data, a silage-maize followed by catch-crop-wheat rotation was simulated with the APSIM model for the RCP 8.5 emission scenario, two time periods (1985–2004 and 2080–2100) and six climate models across the Kaituna catchment in New Zealand. Results showed that direction and magnitude of climate change impacts, and the response to adaptation, varied spatially and were affected by rotation carryover effects due to agronomical (e.g. timing of sowing and harvesting) and soil (e.g. residual nitrogen, N) aspects. For example, by adapting maize to early-sowing dates under a warmer climate, there was an advance in catch crop establishment which enhanced residual soil N uptake. This dynamics, however, differed with local environment and choice of short- or long-cycle maize genotypes. Adaptation was insufficient to neutralize rotation yield losses in lowlands

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but consistently enhanced yield gains in highlands, where other constraints limited arable cropping. The positive responses to adaptation were mainly due to increases in solar radiation interception across the entire growth season. These results provide deeper insights on the dynamics of climate change impacts for crop rotation systems. Such knowledge can be used to develop improved regional impact assessments for situations where multi-crop rotations better represent predominant agricultural systems.

1. Introduction

Agriculture is one of the most sensitive economic sectors to climate change (Godfray et al., 2010). Historically, agronomic practices have developed and evolved under relatively stable climatic conditions. Therefore, with the fast pace of climatic changes observed in the past decades (Smith et al., 2015) and projected for the next century (IPCC, 2007a) current agronomic practices will be challenged and will require refinement. In climate change impact assessments for agricultural systems, changes to agronomic management are often formulated as farm-level reactive interventions to manage risks and/or enhance productivity (IPCC, 2007b). The inherent capacity that individual farmers have to adapt agricultural practices to changing conditions is a valuable knowledge-asset that influences regional and global food security. For example, risks due to weather variability between years are often managed by shifting sowing dates, genotype choices or the combination of crop species in a rotation (Porter et al., 2014). It is, therefore, critical to develop methods to include farmers' tactical adaptation into climate change impact assessments to assess their effect on the direction and magnitude of estimated climate change impacts (Ewert et al., 2015). Biophysical process-based models are one of the most commonly applied tools for assessing crop responses to climate change impacts and adaptation (Rosenzweig et al., 2013). For example, biophysical models often show large yield losses due to climate change when adaptation is not considered for maize crops (Bassu et al., 2014; Liu et al., 2016), the cereal with the largest global production (FAOSTAT, 2017). In contrast, when adaptations are considered, negative impacts of climate change are often minimized or reverted, although results vary across and within studies (Butler and Huybers, 2013; Challinor et al., 2014). Tactical management adjustments by maize growers, particularly the use of long-cycle genotypes, were estimated to increase maize yields from 7% to 57% in Northeast China, depending on the sub-region assessed (Zhao et al., 2015b). Additional gains from adaptation were projected when the widening of the growth season due to a warmer climate was considered, as the analysis of entire season provides a more comprehensive quantification of trade-offs with previous and following crops in multi-crop sequences (Fletcher et al., 2011). A literature review by White et al. (2011) has shown that ~60% of the assessed climate change impact studies included for some representation of adaptation, and a mere 5% considered crop rotation sequences specifically. This is an important gap because in many agricultural regions worldwide, including New Zealand, multi-crop rotation sequences to improve productivity and minimize environmental impacts are commonplace. It is unclear the extent of the carryover effects of one crop to the next, e.g. through the timings of crop transitions (Fletcher et al., 2011) and residual soil water and nitrogen conditions (Teixeira et al., 2015) that can influence adaptation assessment results. This understanding is particularly important for regional assessments that require aggregation of model inputs and/or results spatially, because adaptation may have contrasting effects on the different crops in the rotation, depending on local environmental conditions. In this study we designed a biophysical modelling case study to assess the effects of farmers' tactical adaptations on crop rotations, across an exemplar catchment in New Zealand where sequences with maize crops are historically practiced. Our aim is to understand how tactical adaptation options influence spatial patterns of climate change impacts across the entire length of a crop rotation. Insights from this analysis are expected to inform large-area impact assessments where complex agricultural systems, such as crop rotations, more accurately represent production systems in practice.

2. Materials and methods

2.1. Study location and agronomic scenario

The modelling experiment was performed across approximately 115,000 ha of the Kaituna catchment, Bay of Plenty, New Zealand (Fig. 1). The catchment represents a typical lowland environment in New Zealand which is occupied by a diverse mix of primary production activities (cropping, horticulture, forestry, dairy, sheep and beef farming) and natural ecosystems (freshwater wetlands and native forests) areas (Ausseil et al., 2016). There is a progressive increase in elevation from the north-eastern coastal areas (near sea level) to the most south-eastern areas at ~800 m above sea level (Fig. 1).

To quantify differences between current and future climate projections, a continuous crop rotation (i.e. without re-setting of soil carbon, nitrogen or water conditions) was simulated across the entire catchment area. The main crop in the rotation was spring-sown maize (*Zea mays*) for silage. An autumn catch crop of forage wheat (*Triticum aestivum*) was sown after the harvest of maize at silage maturity. The selection of this specific rotation aimed solely to represent a plausible crop sequence, without any intent to depict either current or future land uses across the catchment, which are largely driven by factors beyond the scope of our investigation (e.g. market forces, infrastructure, local culture and land use regulations). Silage maize followed by a winter cereal was found to be one of the most productive, i.e. >30 t (t; 1000 kg) of dry matter (DM) per ha/year, crop rotations across New Zealand (de Ruiter

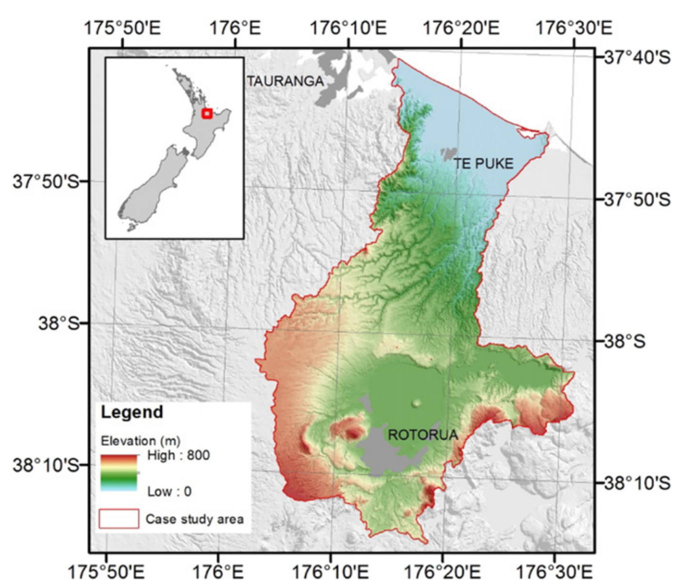

Fig. 1. Case-study area in the Kaituna catchment, Bay of Plenty, New Zealand. The map shows contrasts in elevation across the catchment area, meters above sea level.

et al., 2010). The simulation of autumn-wheat as the catch crop following maize depicted a best management practice aimed at reducing the risk of nitrogen (N) leaching losses in winter-spring and provide extra forage/feed as whole crop cereal silage (Fraser et al., 2013; Malcolm et al., 2016). Catch crops are sown to minimize the fallow (i.e. bare soil) period during winter, providing multiple agronomic and environmental benefits. Specifically, fast canopy cover development minimizes weed establishment, reduces erosion risks and acts as a plant sink for excess soil N that could otherwise be leached and contaminate groundwater (Teixeira et al., 2016a; Tonitto et al., 2006). For the context of our study, we assume that farmer's management decisions priorities the annual productivity of silage-maize rotation, so that the sowing and harvest of the catch crop are subject to maize completing its development to silage maturity or crop termination (e.g. senescence due to frost). Following previously developed rationale to develop automated sowing rules (Dobor et al., 2016), we empirically assumed that farmers would sow silage maize as early as possible in spring (from 1 September) until late-summer (1 January) once the 15-day running mean air temperature was >13 °C. These empirical rules aimed to reduce the risk of exposure to early-spring frost damage and advance sowing dates under warmer conditions. In addition, to represent delays in sowing caused by unsuitable soil conditions (Aurbacher et al., 2013), crop sowing was not allowed on rainy days (>10 mm) or saturated soils, assumed as when soil moisture during a given day exceeds the plant available water capacity in the top 150 mm by 5%. In New Zealand's North Island, maize is typically grown without irrigation, therefore only rain-fed conditions were considered in our simulations. These crop management rules aimed to empirically represent crop husbandry practices surveyed from local maize growers (Fig. 4 and Supplementary material).

2.2. Climate data and climate change scenarios

Daily time-resolution climate data for approximately 20-year time periods, within 45 grid-cells across the catchment at a 5 arc minute spatial-resolution (~5 km grid), was used as input for the biophysical model (Section 2.3). Model outputs for a historical period (1980–1999) were first produced in response to measured climate data interpolated to the 5 arc minute resolution from the national grid of weather stations - the Virtual Climate Station Network (VCSN) from the National Institute of Water and Atmospheric Research (NIWA) of New Zealand (Sood, 2015). These model runs were solely used to evaluate spatial patterns of absolute crop yields in response to historical weather data. Climate change impacts were then calculated from similar spatio-temporal resolution data from six selected General Circulation Models (GCMs), from the fifth phase of the Coupled Model Intercomparison Project (CMIP5), by comparing baseline (1985–2004) and future (2080–2100) periods of analysis. All gridded climate datasets were bias corrected and downscaled to the 5 arc minute grid-cell spatial-resolution across the catchment using a Regional Climate Model (Tait et al., 2016). Simulated baseline weather conditions across the catchment ranged from 7 to 10 °C for minimum temperature, 16 to 19 °C for maximum temperature, 1270 to 2460 mm/year for rainfall and 12 to 17 MJ/m^2 per day for solar radiation (Fig. 2). For the future time-slice, we considered only a single Representative Concentration Pathway (RCP), specifically RCP 8.5 (Meinshausen et al., 2011). The choice of RCP 8.5 during the end of century aimed to assess crop rotation responses to the most extreme climatic changes driven by available emission scenarios. The RCP 8.5 represents the upper limit of available greenhouse gas concentration scenarios, resulting in an average increase in temperature by 2 to 3.6 °C from the historical period to the end of the century period for the catchment (Fig. 2). The average range of changes due to climate change for RCP 8.5, across the six GCMs and 45 grid-cells, was 2.0 to 3.3 °C for minimum temperature, 2.1 to 3.6 °C for maximum temperature, −250.7 to 270 mm/year for rainfall, and −0.5 to 0.31 MJ/m^2 per day for solar radiation.

The uncertainty around future climate model predictions captured in our study can be illustrated by the wetter future projected by half of the GCMs (HadGEM2-ES, BCC-CSM1.1 and NorESM1-M) in comparison with drier conditions in the other models (CESM1-CAM5, GISS-EL-R and GFDL-CM3). The mean atmospheric CO_2 concentration for the 20-year period time-slices was 353 ppm for the baseline and 1032 ppm for the future climate change scenario.

2.3. Modelling framework

The Agricultural Production Systems sIMulator (APSIM) model version 7.7 (Holzworth et al., 2014) was used to perform all simulations in this study. In brief, APSIM is a biophysical process-based model that simulates crop growth and development (and corresponding carbon, water and nitrogen dynamics in the plant and the soil) in response to daily weather input data. The model is composed of multiple modules that represent specific processes at the plant (e.g. canopy development and flowering time), soil (e.g. drainage and N mineralization) and farmer management decision levels (e.g. sowing time and genotype choice). The model has been previously calibrated and tested for a wide range of climatic conditions, including sowing dates and genotype combinations as required for this study (Archontoulis et al., 2014; Teixeira et al., 2016a,b; Zhao et al., 2014). The main model output analyzed was total aboveground biomass yield for the two crops, spring-sown maize and autumn catch-crop wheat, measured as t DM/ha per year. Complementary model outputs were produced to support the interpretation of yield differences. These were average temperature during crop growth (°C), sowing day of the year (DOY, 0–365), crop cycle length (days), average growth rate (kg DM/ha per day), radiation interception (MJ/m^2 per year), radiation use efficiency (RUE, g DM/MJ), maize silage harvest index (HI, 0–1) and catch-crop N uptake during winter (kg N/ha per year). Prior to comparing baseline and future climate runs for the six GCMs, long-term yield simulations were evaluated by using interpolated historical weather data (1971–2000), that represents the closest values to weather station measured data, for each grid-cell. The historical climate data from the Virtual Climate Station Network (VCSN) was developed by the National Institute of Water and Atmospheric Research (NIWA) of New Zealand (Sood, 2015).

The biophysical model was set up to simulate annual yields of a continuous silage-maize/catch-crop wheat rotation (Section 2.1) in response to 20 years of daily weather variables in each grid-cell (Fig. 3). To investigate the effect of farmer's tactical adaptation, APSIM runs were performed considering genotype choice (short- and long-cycle hybrids, Supplementary material) and two extremes of sowing date adaptation (with and without early sowing in response to warmer conditions in RCP 8.5). For the non-adapted sowing date model runs in the end of the century period, maize crops were sown on the average date estimated during the 20-year baseline climate runs for each grid-cell and GCM combination. Temperature requirements (i.e. thermal-time accumulation in degree-days, °Cd) from emergence to end-of-juvenile period ("tt_emerg_to_endjuv" APSIM-maize parameter) were 130 °Cd for the short-cycle hybrids and 250 °Cd for long-cycle hybrids. The range in sowing dates and genotype choices currently used by farmers in the climate zone (Teixeira et al., 2016b) and latitudinal range of the Kaituna catchment were sampled through an online national survey in partnership with the Foundation for Arable Research (FAR, www.far.org.nz). Data on crop management collected from 39 respondents illustrated the wide distribution of sowing dates and genotype selection already utilized and silage yields obtained by maize farmers in this climate zone (Figs. 4, 1S in Supplementary material).

For catch crop wheat (C_3 species), growth rates were assumed to increase with atmospheric CO_2 concentration, adjusted by temperature, by scaling radiation use efficiency (RUE) as per APSIM-wheat default parameterization (O'Leary et al., 2015). In contrast, no CO_2 impact on RUE was considered for silage maize (C_4 species) and RUE is empirically adjusted by air temperature as per APSIM-maize default

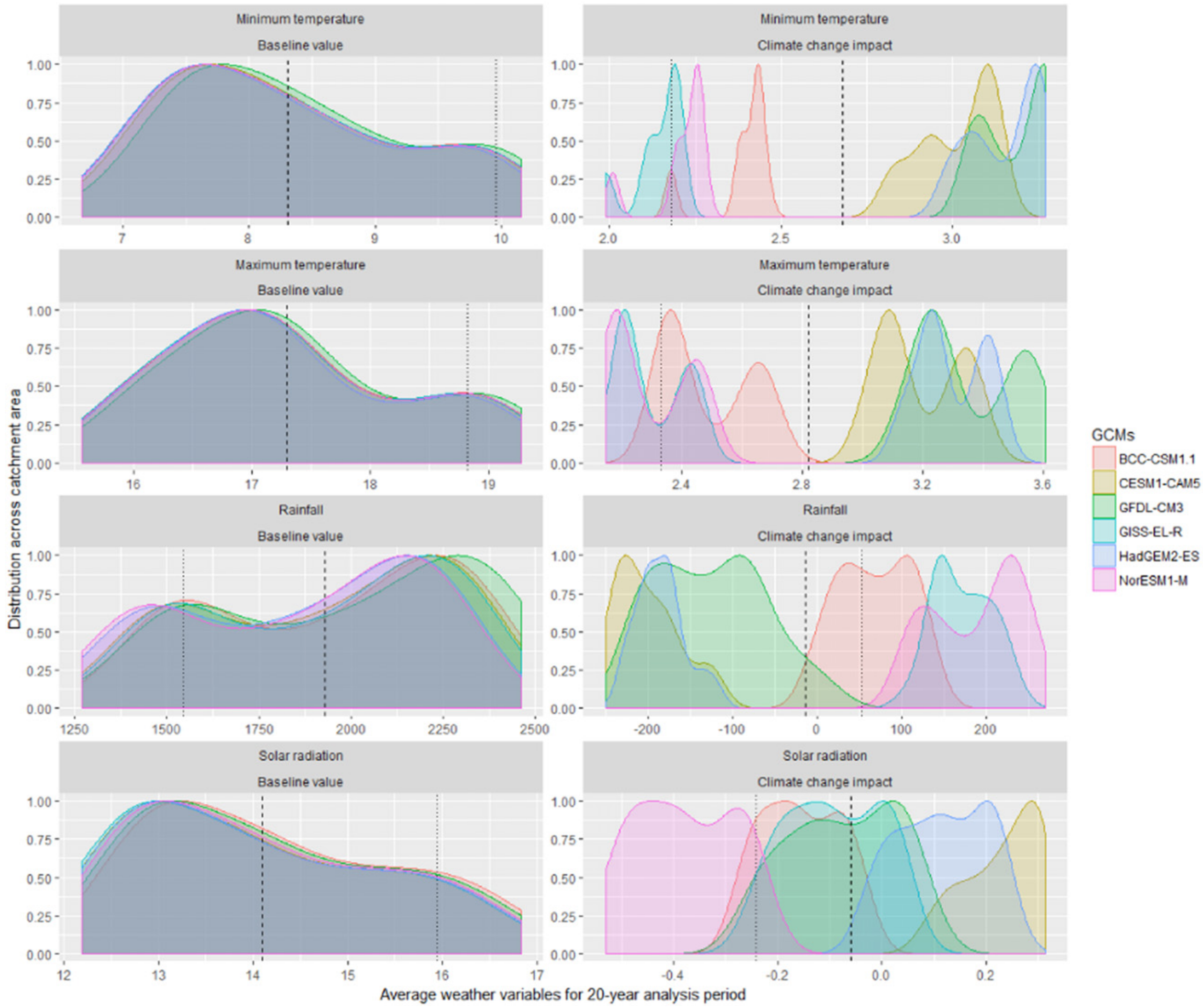

Fig. 2. Scaled distribution of climate variables across the Kaituna catchment, Bay of Plenty, New Zealand grid-cells for baseline values (1985–2004) and relative changes due to climate change for a future scenario (Representative Concentration Pathway, RCP 8.5, 2080–2100) considering six Global Circulation Models (GCMs). Lines indicate the mean (long dash) and mode (short dash) value for the six GCMs across the catchment. Weather variables are temperature (°C), solar radiation (MJ/m^2 per day) and rainfall (mm per year).

parameterization. For both crops, transpiration efficiency (TE) was arbitrarily assumed to increase to a maximum of 37% for maize and 69% for wheat the at atmospheric CO_2 concentration of 1032 ppm, in relation to a 350 ppm baseline.

Simulations were performed considering a single hypothetical soil type with high water storage across the catchment. Volcanic soils predominate across the catchment which are deep and have high water storage capacity (Molloy, 1988). We represented that with a high plant available water holding capacity (WHC) of 160 mm/m to a depth of 1.8 m, with similar parameterization across depths (Table 1S in Supplementary material). Final model results were also analyzed in relation to landscape aspects, specifically elevation (Fig. 2) and the land use capability based on the Land Resource Information Systems (LRIS) Portal (Newsome et al., 2008). Specifically, each of the 45 grid-cells where classified for suitability for arable cropping (e.g. relief favorable for mechanization) based on the LRIS land use classes (LUC) which were aggregated into lands suitable for arable (LUC classes 1 and 2), moderately suitable for arable (LUC classes 3 and 4) and unsuitable for arable (LUC classes > 4) cropping. Datasets were analyzed and graphically displayed using the statistical language R (R Development Core Team, 2016).

3. Results

3.1. Baseline climate estimates of crop yield across catchment

For historical climate, yield estimates ranged from 10 to 28 t DM/ha for silage maize and 5 to 9 t DM/ha for catch crop wheat (Fig. 5). The use of long-cycle maize hybrids increased maximum maize yields by ~18% in lowlands (warmer areas) but reduced minimum yields in highlands (cooler areas) by ~28%. Aboveground biomass yields of catch crops were highest when preceded by short-cycle maize hybrids in lowlands. In contrast, catch crops yield estimates were highest in highlands when preceded by long-cycle maize hybrids, which yielded poorly under these cold conditions as discussed in Section 4.2. For both crops, baseline climate conditions created sufficiently contrasting yield gradients as necessary to test the impact of adaptation options under climate change scenarios.

3.2. Climate change impacts and response to adaptation

The magnitude and direction of climate impacts relative to the baseline climate largely differed across the catchment (Fig. 6). Reduction in

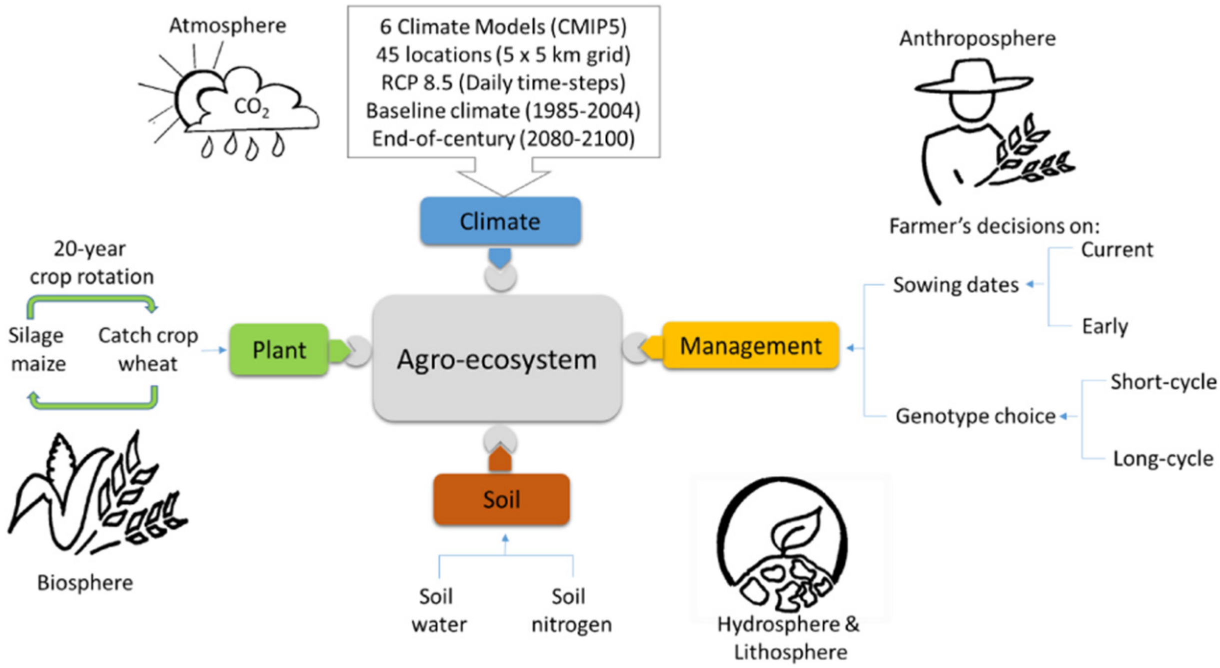

Fig. 3. Schematic representation of the modelling framework developed for this study. The RCP is a Representative Concentration Pathway. The CIMIP5 is the Coupled Model Intercomparison Project for global coupled ocean-atmosphere General Circulation Models (GCMs).

yields was estimated for both crops in lowland coastal areas due to climate change effects. In contrast, highlands showed yield gains in response to climate change both for pooled GCM averages (Fig. 6) and individual GCMs values (Fig. 7).

In most cases, the adaptation of silage-maize sowing dates (early-sowing) minimized yield losses or increased yields gains for both crops in the rotation, regardless of the maize genotype used (Fig. 7). In contrast, the use of long-cycle maize genotypes reduced negative climate change impacts for maize but increased them for catch crop wheat. Differences among the six GCMs, although present, were of relatively lower magnitude than the differences among locations, crops and adaptation assumptions.

Yield responses to climate change showed both trade-offs and synergies between the two crops in rotation (Fig. 8). For non-adapted sowing dates, the highest frequency of negative impacts on both crops occurred (bottom-left red quadrant in Fig. 8), particularly at lowlands (<200 m). The shift to long-cycle hybrids allowed positive responses of maize yield to climate change, particularly for highlands, but increased yield losses for the catch crop (trade-off in bottom-right yellow quadrant). In contrast, when sowing dates were adapted yield gains occurred for both crops across a large number of locations (top-right green quadrant), although smaller yield losses still occurred for both crops in lowlands. The trade-offs in yield response to climate change for the two crops in the rotation (top-left/bottom-right yellow quadrants) occurred mainly in highlands without sowing-date adaptation or in lowlands when sowing dates of short-cycle hybrids were adapted. The degree of uncertainty due to GCMs was greater for highlands than lowlands (Fig. 8).

When considering the total crop sequence yield, adaptation of maize sowing dates consistently minimized negative climate change impacts across the rotation (Fig. 9). For example, yield losses would occur at elevations <500 m without adaptation but this shifted to <150–200 m when sowing date adaptation was considered. The highest estimates of yield gain due to climate change, which increased with the elevation

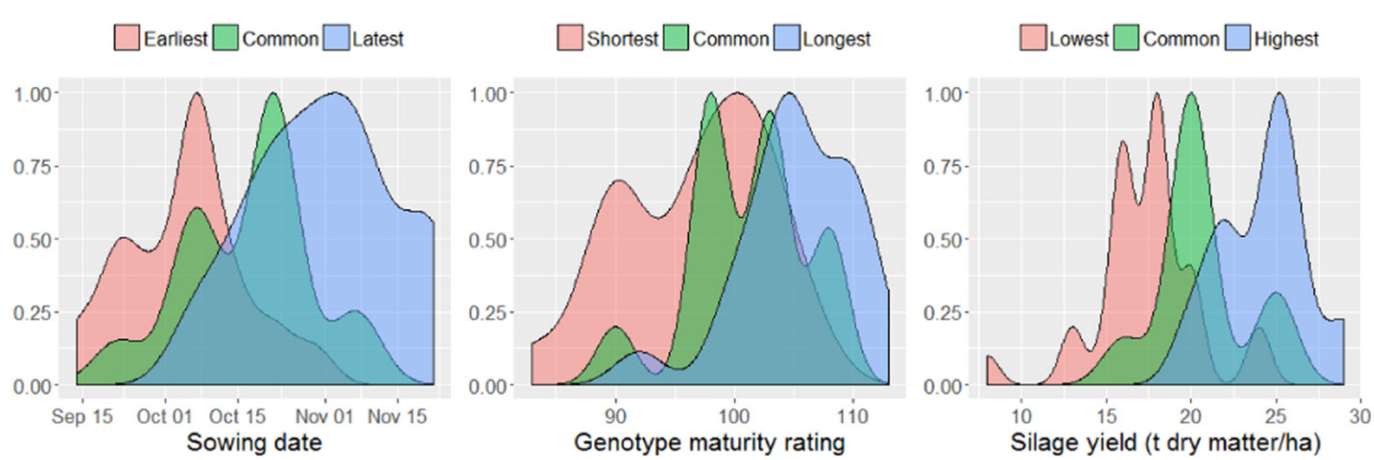

Fig. 4. Scaled distribution of maize sowing dates, relative genotypes maturities (80 = early-cycle and 120 = late-cycle genotype) and silage yields (t DM/ha) reported from a survey with 39 local farmers within the climate zone of the Kaituna catchment, Bay of Plenty, New Zealand (latitudes −36.64 to −38.64°S). Categories represent farmer's personal perception of most common (green) and extreme (red and blue) values of variables during multiple years of maize cropping.

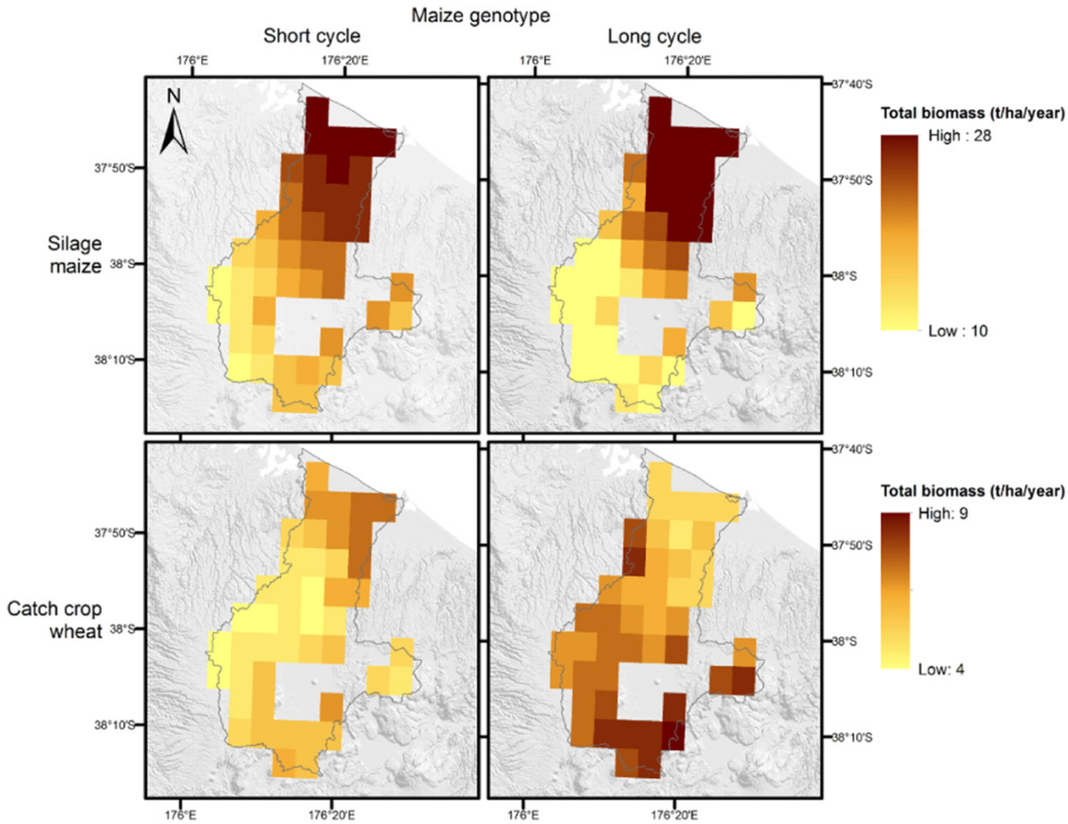

Fig. 5. Baseline aboveground dry matter yields (t DM/ha) simulated for a silage-maize followed by catch crop wheat crop across the Kaituna catchment in New Zealand. Grid-cell values show mean yield for a 20-year model run from 1985 to 2010 using the historical climate from the ERA-40 dataset. Non-simulated grid cells refer to water bodies in the catchment.

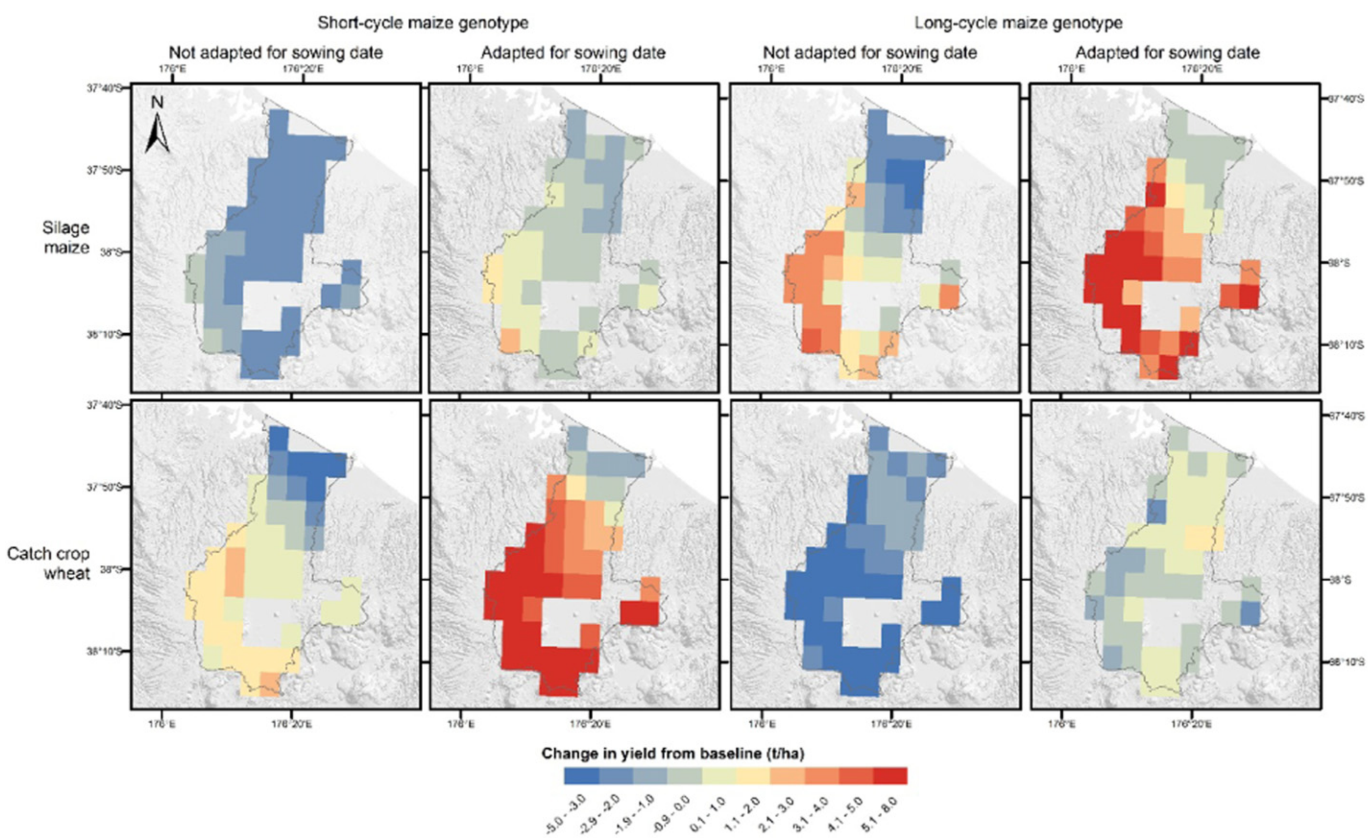

Fig. 6. Spatial variability of climate change impacts on total biomass yields of silage maize and catch crop wheat across the Kaituna catchment in New Zealand. Values are averaged across ~ 20-years and six Global Circulation Models (GCMs). Individual GCM values and catchment means are shown in Fig. 7. Non-simulated grid cells refer to water bodies in the catchment.

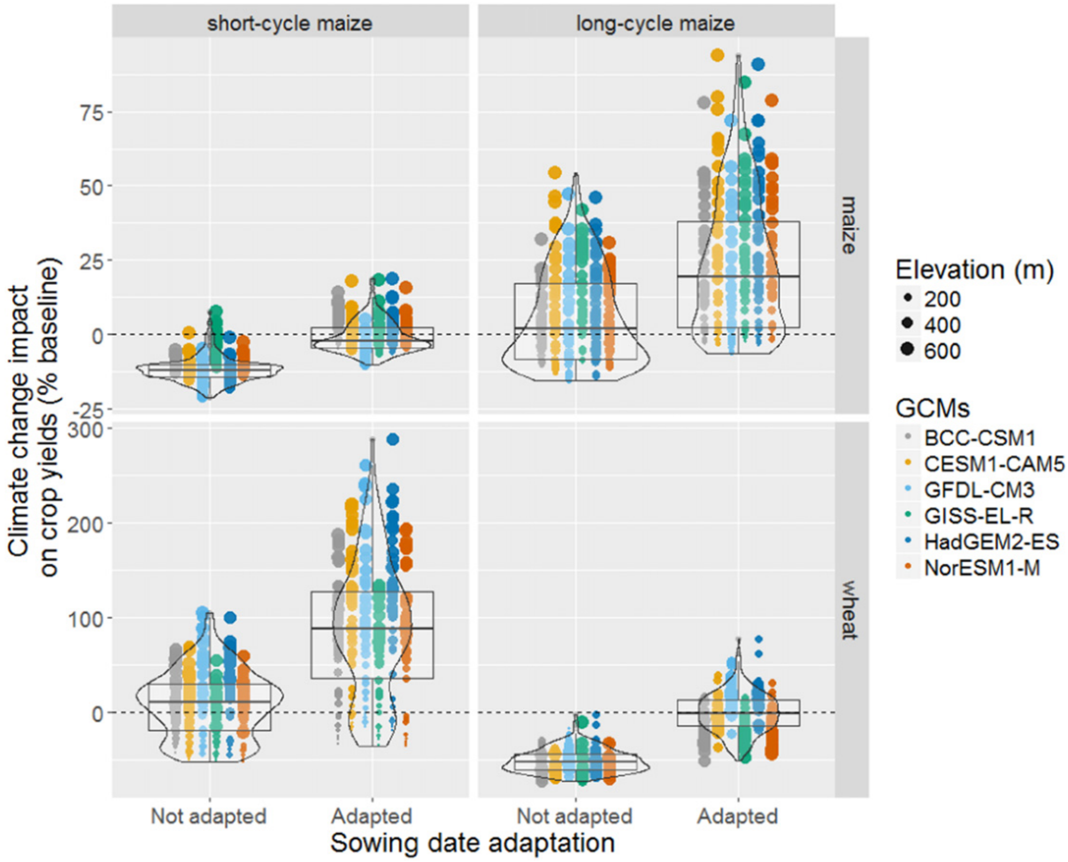

Fig. 7. Simulated relative climate change impact (% baseline yields) for a crop rotation of silage-maize followed by a wheat catch crop. Points represent individual grid-cells in the Kaituna catchment, Bay of Plenty, New Zealand. Model results consider climate input from six different Global Circulation Models (GCMs). Box- and violin-plots show distribution of estimates for all grid-cells and GCMs across the catchment. Box-edges represent the 25th and 75th percentile, central line in the box is the median value.

of catchment, occurred in lands currently classified as moderately to unsuitable for arable cropping (Fig. 9).

A selection of yield-related underlying model variables was used to interpret the spatial patterns of crop rotation responses to climate change adaptation (Table 1). The extreme climate change scenario considered (RCP 8.5 in 2080–2100) caused a 38–40 days earlier sowing of silage maize than baseline. Early spring sowing of maize reduced the temperature which crops were exposed to during the growth cycle from 0.9 °C (short-cycle) to 1.6 °C (long-cycle). In contrast, temperatures were slightly higher (~0.75 °C) during catch crop growth that was

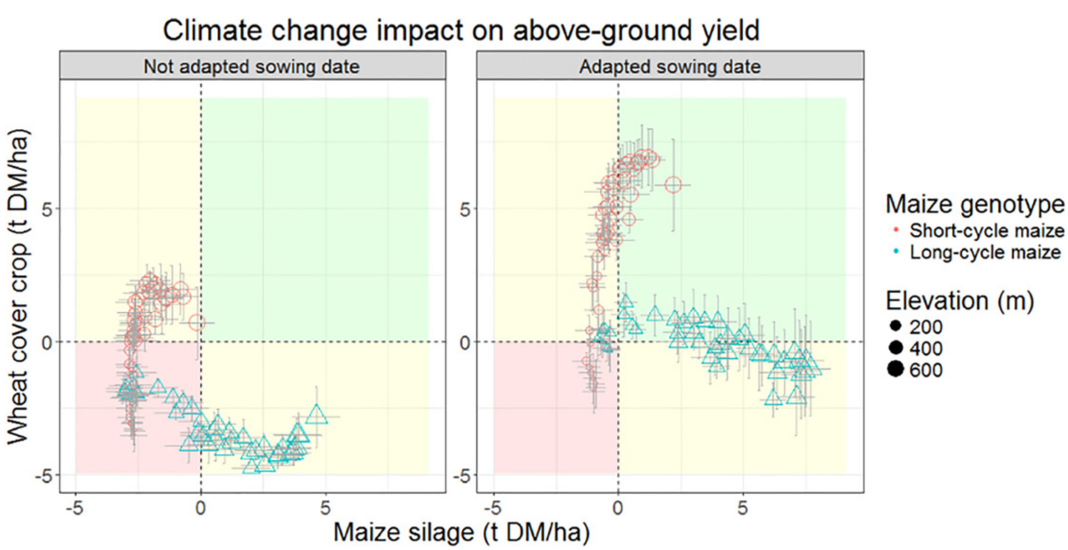

Fig. 8. Simulated climate change impacts on aboveground biomass (t DM/ha) for individual grid-cells for short- (triangle) and long-cycle (circle) maize genotypes. Points represent ~20-year averages for a continuous crop rotation in the Kaituna catchment (silage-maize followed by catch crop wheat). Grey bars represent uncertainty from the 6 Global Circulation Models (GCMs) as one standard deviation. Graph quadrants show areas of yield loss for both crops (red), yield gain for both crops (green) and trade-off areas for climate change impact on yields (yellow). Symbol size represents altitude.

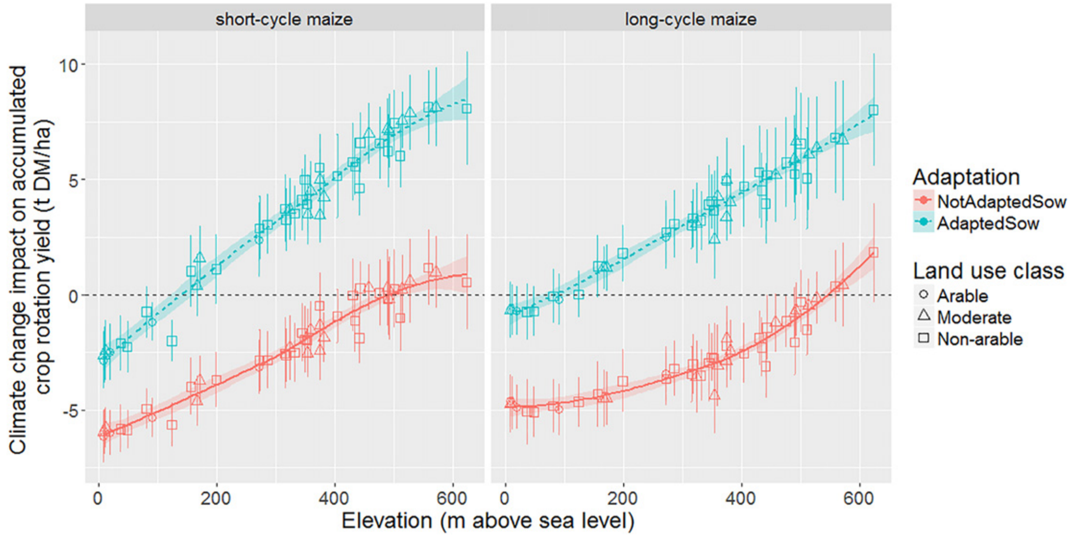

Fig. 9. Simulated climate change impacts on aboveground biomass (t/ha) for the entire rotation sequence (silage-maize plus catch-crop wheat). Points represent 20-year averages for a continuous crop rotation in the Kaituna catchment, Bay of Plenty, New Zealand. Error bars represent uncertainty from the six Global Circulation Models (GCMs) as one standard deviation.

also sown earlier (26–28 days) following silage-maize harvest. The longer growth period of early-sown catch crops enabled greater N uptake during the winter period (58 to 78 kg N/ha). The main mechanism by which adaptation influenced yields was through an increase in radiation interception (132 to 587 MJ/m^2), with much less prominent impacts of RUE and HI, although responses differed depending on location across the catchment (Supplementary material).

4. Discussion

Socio-economic conditions of regions that rely heavily on agricultural production, such as the Kaituna catchment in New Zealand, will be influenced by how effectively adaptation to climate change develops in the following decades (Godfray et al., 2010). It is therefore critical to better understand how to factor adaptation options into climate change impact assessments (Campbell et al., 2016), particularly for production systems that have worldwide relevance, but are less represented, such as crop rotations (Ewert et al., 2015; White et al., 2011). Our study provides the first comprehensive investigation of spatial patterns of adaptation responses in crop rotations. Insights from this study can inform regional spatial modelling assessments where multiple crops are grown in sequence.

Table 1
Absolute baseline values and effects of maize sowing date adaptation on selected yield-related variables. Ranges across the catchment for a long-cycle silage maize genotype (SM) and catch crop wheat (CC) rotation.

Variable	Crop	Catchment average (baseline climate)			Adaptation effect[a]		
		Min	Mean	Max	Min	Mean	Max
Temperature during growth cycle (°C)	SM	14.7	16.2	17.8	−1.5	−0.9	0.0
	CC	8.6	10.2	12.3	0.6	0.8	0.9
Sowing day of year (0–365)	SM	289	322	346	−44	−40	−33
	CC	83	119	129	−33	−28	−20
Crop cycle length (days)	SM	140	155	166	4	8	13
	CC	182	191	201	20	28	33
Growth rate (kg DM/day)	SM	78	124	170	−1	13	23
	CC	23	32	43	5	12	19
Radiation interception (MJ/m^2)	SM	911	1411	1913	142	208	288
	CC	965	1096	1270	246	508	588
RUE (g DM/MJ)	SM	1.2	1.4	1.5	−0.01	0.00	0.02
	CC	0.5	0.6	0.7	−0.8	−0.5	−0.1
Maize HI (0–1)	SM	0.0	0.3	0.5	−0.01	0.01	0.08
Catch crop N_{up} (kg/ha)	CC	45	68	96	24	58	85

[a] The "adaptation effect" was calculated as the difference between adapted and non-adapted maize sowing dates for the end of the century period. The mean, minimum (Min) and maximum (Max) values were estimated across all 45 grid-cells of the catchment and six General Circulation Models (GCMs). RUE is the radiation use efficiency of aboveground biomass for global solar radiation. HI is the harvest index. N_{up} is nitrogen uptake. DM is dry matter.

4.1. Spatial variability of impact and adaptation responses

The first insight from our analysis is that the magnitude and direction of crop yield responses to climate change, and the effectiveness of adaptation, can have large spatial variation at catchment scale (Fig. 6). The spatial variability in adaptation responses, also found for other crops in global scale analyses (Deryng et al., 2011), highlights the importance of tailoring adaptation interventions to local environmental and socio-economic conditions (Olesen et al., 2011; Trnka et al., 2011). For example, for the climatic conditions of our study, crop yields in lowlands were more negatively affected by climate change, particularly when no adaptation was considered, due to shortening of crop cycles as temperature increased (Table 1). Yield losses continue to occur in lowlands even with the full suite of adaptive options (early-sown long-cycle maize genotypes). This contrasted with highlands, where yield gains were estimated in response to climate change, as future warmer conditions minimized low temperature constraints on crop growth. The implication of these results is that adaptation responses should not be aggregated across geographic regions with contrasting environmental conditions (Fig. 1), as effects may cancel out as illustrated in the Kaituna catchment (e.g. Table 1). This wide range of adaptation responses occur due to interactions between genotype/management/environmental aspects of the cropping system and can be better captured by performing analyses within homogeneous climate zones (e.g. Teixeira et al., 2016b) and by considering other biophysical/socio-economic aspects that may influence local adaptive capacity (White et al., 2011). Such considerations are likely to reduce potential biases during the aggregation of results, often necessary in regional climate impact studies (Ewert et al., 2011; Hoffmann et al., 2014; Zhao et al., 2016).

4.2. Adaptation of crop rotations

The second insight from our analysis is that by considering tactical adaptation within a crop rotation context, carryover effects extend beyond the adapted crop in the sequence. For example, early-sowing of long-cycle maize genotypes not only increased resilience of the spring crop to climate change, as shown in many studies (Assefa et al., 2012; Dobor et al., 2016; Lana et al., 2016; Tao et al., 2014; Wolf and van Diepen, 1994; Zhao et al., 2015b), but also affected how the following catch crop responded to climate change (Fig. 7). Early sowing had a consistent positive effect on yield response of the full rotation to climate change (Fig. 9). However, it was not possible to generalize climate change impacts for both crops because total rotation yield emerged both from trade-offs and similar direction responses, largely depending on local environmental conditions (Fig. 7). This reinforces the value to represent continuous crop rotations in regional adaptation assessments, instead of monocultures, when these systems are locally relevant (Kollas et al., 2015). In agreement with Fletcher et al. (2011), the main mechanism by which adaptation influenced resilience to climate change was by increasing solar radiation interception by the crop canopy (Table 1). This occurred as a combination of both agronomic and physiological responses such as lengthening the growth period and allowing the crops to grow closer to their optimal temperatures. The complexity of carryover responses in rotations, and the imperfect representation of these in biophysical models (Kollas et al., 2015), suggests that careful interpretation of results is necessary when considering adaptation in crop rotation simulations. For example, in our study there were locations where the use of long-cycle maize genotypes may not be the most adequate adaptation option, even when net yield gains occurred. In highlands, large increases in catch crop yield were estimated when preceded by long-cycle maize genotypes (Fig. 5). This was caused by the high frequency of low yields for long-cycle maize genotypes under cold highland conditions, which implied an excess of N fertilizer being carried to the following (often N limited) catch crop, boosting its growth. This could be considered as an inefficient use of N fertilizer, and illustrates the complexity of carryover effects that can occur when factoring adaptation options into crop rotation assessments. In addition, even high relative yield increases of long-cycle genotypes in highlands due to climate change (up to 80%, Fig. 7) may be insufficient to reach minimum thresholds for economic viability due to very low (<10 t/ha) baseline yields (Fig. 5). These examples emphasize the need for judicious interpretation of results, and extensive model testing against quality datasets (Kollas et al., 2015), when simulating more complex agricultural systems, as continuous crop sequences, to ensure that sensible responses are represented (Teixeira et al., 2015). In agreement with White et al. (2011), our results show the importance of considering benefits of tactical adaptation beyond crop productivity, such as for the environmental benefits of increases in catch crop N uptake potential with adaptation (Table 1), and the financial returns from improved yields which are likely to be greater than the additional costs of the tactical adaptation options evaluated in this study.

4.3. Scope, limitations and implications of this case-study

Our results should not be interpreted as projections of climate change impact for the Kaituna catchment. There are important aspects that impact yields in response to climate change which were not considered in our analysis. These include, for example, the susceptibility to extreme events (e.g. heat waves, floods and storms) and biotic stresses (Ewert et al., 2015). Although a sensible model performance was observed for historical climate when comparing simulations with reported yield ranges for both maize (Teixeira et al., 2014; Fig. 4 and Fig. 1S in Supplementary Material) and winter cereal catch crops (Malcolm et al., 2016; Teixeira et al., 2016a) in New Zealand, uncertainty in yield estimates is likely to increase for future periods when other stress factors become increasingly relevant. The aim of our study was to gain a deeper understanding of methodological considerations for including adaptation into spatially-explicit crop rotation simulations. Therefore, such simplifications in the representation of the agricultural system were necessary to constrain simulation complexity and focus on adaptation effects. In this context, the rotation sequence modelled does not intend to represent current nor future land use projections for the region. Other socio-economic drivers beyond the scope of our study such as market trends, regional land use policies and local culture are strong drivers for adoption of cropping system practices. The use of crop yield as the main impact variable is also a simplification of the economic, environmental and social dimensions of adaptation to climate change in agricultural systems. In reality, market value of silage from maize or catch crops depends on forage quality and seasonal demand for feed, not only total rotation biomass, as in Fig. 9. Similarly, for catch crops, there is the additional ecosystem benefit of minimizing risk of N leaching losses in winter (Table 1). White et al. (2011) provide a comprehensive list of other important aspects to be considered in adaptation studies such as the availability of soil- and water-resources and the socio-economic conditions of the target environment. In our study, we extend the analysis of adaptive responses by exploring key underlying mechanisms explaining yield differences (Table 1). These however do not capture all possible effects of crop rotations (Kollas et al., 2015) and catch crops (Teixeira et al., 2016a) on agricultural systems, such as the influence of weeds, pathogens and insects on yield loss. For a comprehensive impact assessment, the use of multiple biophysical models, climate scenarios (Kollas et al., 2015) and soil types (Folberth et al., 2016) would be therefore required. Nevertheless, our results show that uncertainty due to climate models' projections were of a relatively smaller magnitude than effects of local environment and adaptation assumptions (Fig. 7). This is because, for the conditions of our study, the magnitude of GCM differences in climate was insufficient to cause large contrasts in stress responses such as from rainfall amounts (Fig. 2) which are represented by non-linear or threshold responses to water supply/demand in the model.

In our analysis, we have only assessed static extremes of adaptation scenarios through limited combinations of genotypes and sowing date adaptation. In reality, there is a delay in the adoption of technological changes which implies sub-optimal and variable degrees of adaptation efficiency across time and space (Easterling et al., 2003). In addition, adaptation often occurs as technology bundles where technologies with synergistic effects are sensibly combined (Assefa et al., 2012; Fleischer et al., 2011). For the climatic zone conditions of the Kaituna catchment, the local farm survey showed that a wide range of sowing dates and maize genotype maturities are already part of current adaptation portfolio (Fig. 4). Alternative adaptation scenarios, such as from investment in improved crop genotypes (Edgerton, 2009), could be considered but require foresights on the pace of future technology development (Ewert et al., 2006). Such considerations extend beyond our study, being particularly important for less intensively managed crop rotations where crops are frequently subjected to water and N limitations, so that carryover of soil conditions may more strongly influence yield and environmental aspects of the system (Teixeira et al., 2015).

Although climate change is a phenomenon of global significance, in many cases decision making on adaption options needs to be tailored locally, considering environmental and socio-economic conditions of the scale of action (Butler and Huybers, 2013; Niles et al., 2015). As highlighted by Lobell (2014), our results illustrate the dual role of adaptation interventions at catchment scale as means to reduce losses (e.g. minimizing yield decline in lowlands) and enhance potential gains (e.g. maximizing yield increase in highlands) in response to climate change. However, the improvement of climatic suitability may not convert completely into tangible yield gains because there are other biophysical or socio-economic constraints that can locally limit agricultural production (Trnka et al., 2011). This was the case for the highlands in our study, where the highest increases in climatic suitability occurred for the full rotation on lands that have limited potential for arable cropping due to their steep relief constraining machinery (Fig. 9). This

implies that the strategic adaptation of expanding cropping areas to lands previously limited by low temperatures, as observed for maize in other agricultural areas (Zhao et al., 2015a), may not fully materialize in situations similar to our case-study and require a broader contextual assessment.

Finally, assumptions necessary to set up management rules (e.g. logic and thresholds used for sowing date optimization), the representation of CO_2 effects on individual crops, and the use of a single soil type may affect both the magnitude and direction of adaptive responses in crop rotations. For example, there is considerable uncertainty in the parameterization of RUE and TE responses to CO_2 for both C_3 and C_4 crops (Vanuytrecht and Thorburn, 2017). Although these assumptions are not expected to largely influence the comparison between adaptation options within a single soil type/time period/climate scenario combination, they are important when comparing levels of these factors. Additionally, the selection of RCP 8.5 during the end of the century aimed to investigate adaptation capacity of crop rotations under the upper boundary of available emission scenarios. This high temperature and high atmospheric CO_2 scenario selection is however where global gridded-model comparison studies also show a higher degree of uncertainty in yield (Rosenzweig et al., 2014). The uncertainty due to these assumptions was not considered in our study but can be systematically investigated through a similar methodological approach in the future. Specifically, adaptation effects on crop rotations under different soils, RCPs and time-periods can be investigated with different modelling approaches (i.e. parameterization and model structure) as previously done for single crops (e.g. Aurbacher et al., 2013; Rosenzweig et al., 2014).

The assessment of potential for adaptation in agricultural systems is essential to quantify the degree of vulnerability to climate change. Our results contribute to the understanding of mechanisms that influence spatial variability in crop rotation responses to tactical adaptation.

5. Conclusions

The inclusion of farmer's tactical adaptation in regional modelling studies that simulate crop rotations can affect the magnitude and spatial distribution of climate change impacts. For the case-study conditions, adaptation options (early sowing of long-cycle maize genotypes) consistently improved total crop rotation yield but were insufficient to completely avoid yield losses in the warm lowland areas. The more complex dynamics of crop rotations in response to climate change, in relation to single crops, implies that carryover effects can occur also due to the factoring of adaptation measures. Individual crops within the rotation responded both with similar or opposite directions to climate change, depending on local environmental conditions. The possible occurrence of such trade-offs and carryover effects highlight the need for careful setting up of management rules when including rotations, and a broader contextual interpretation of simulated results, to avoid introducing systematic biases in regional model studies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2017.10.247.

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